Journal of Defense Technology and Engineering, Vol. 1 No. 1, July (2025) pp. 41-51

Published by: Fakultas Teknik dan Teknologi Pertahanan, Universitas Pertahanan RI

Journal of Defense Technology and Engineering

Journal homepage: www.research.idu.ac.id/index.php/jdte

Predicting interprovincial rice food security in Indonesia as a Pillar of National Defense using the random forest regressor algorithm

Bagus Hendra Saputra[1], Ahmad Eryan Firdaus[2]

[1] Teknik Elektro, Universitas Pertahanan Republik Indonesia, Bogor, Indonesia

[2] Informatika, Universitas Pertahanan Republik Indonesia, Bogor, Indonesia

ARTICLE INFO

Article history:

Received July 01, 2025
Revised July 20, 2025
Accepted July 30, 2025

Keywords:

Food Security;
National Defense;
Random Forest;
Rice.

ABSTRACT

This study investigates interprovincial rice food security in Indonesia as a strategic pillar of national defense. Using a quantitative predictive approach, the Random Forest Regressor algorithm was applied to multidimensional data from all provinces, incorporating variables such as rice expenditure per capita, rice price, production, population, consumption, and harvested area. The results show significant disparities between provinces: surplus regions such as East Java, Lampung, and South Sulawesi contrast sharply with deficit areas like Jakarta, Papua, and Bangka Belitung. Feature importance analysis reveals that supply-side factors, particularly harvested area (50.5%) and production (33.2%), are the most decisive, while demand-side factors have weaker influence. Model evaluation achieved an R^2 of 0.8239, confirming strong predictive reliability. These findings underscore that rice food security is not only an economic and social issue but also a critical aspect of non-military defense. Strengthening predictive systems and interprovincial distribution networks is essential to ensure resilience against disruptions from disasters, conflicts, or geopolitical instability. The study highlights the practical value of machine learning models in guiding evidence-based policy to secure national food sovereignty.

Corresponding Author:

Bagus hendra saputra,
Teknik Elektro Afiliasi
Universitas Pertahanan Republik Indonesia
Kawasan IPSC Sentul, Sukahati, Kec. Citeureup, Kabupaten Bogor, Jawa Barat 16810, Indonesia.
bagus.saputra@idu.ac.id

1. INTRODUCTION

Food security has long been regarded as one of the main foundations of sustainable development and national stability (Clapp et al., 2022; Pachapur et al., 2020). In the Sustainable Development Goals (SDGs), particularly the second goal of Zero Hunger, food is an important indicator in measuring the success of global development (Atukunda et al., 2021). In Indonesia, rice occupies a strategic position because it is the staple food for most of the population, so that price stability and availability have a direct impact on inflation, poverty, and social stability (Alifnur Harmawan & Mulyati, 2024; Yusrin, 2023). Furthermore, rice food security is also closely related to the dimension of non-military defense, as food supply instability can trigger social unrest, reduce community resilience, and even weaken national sovereignty (Cook & Nair, 2021; Hidayana et al., 2022). Thus, strengthening a data-based food security prediction system is a strategic necessity to strengthen the nation's competitiveness and resilience.

Although the Indonesian government has launched various food security programs such as the Government Rice Reserve (CBP), the Food Estate program, food diversification, and strengthening distribution through Bulog and the National Food Agency (Bapanas), the reality on the ground still shows significant disparities (Alta, 2023; Widowati et al., 2024). Disparities between provinces in terms of availability, consumption, prices, and distribution of rice continue to occur, creating areas of surplus and deficit that are not balanced (Fitrawaty et al., 2023; Fristin & Supanto, 2021). This situation becomes even more complex when viewed from a national defense perspective: in an uncertain geopolitical context, including the potential for regional and global conflict, Indonesia's dependence on food imports is a serious vulnerability. If international trade routes are disrupted due to war or embargoes, Indonesia will face great difficulties in meeting its food needs, making domestic production independence an absolute requirement for ensuring national security (Ben Hassen & El Bilali, 2022; Larasati & Hana, 2025).

This study aims to develop a model for predicting inter-provincial rice food security in Indonesia using the Random Forest Regressor algorithm. By integrating key variables such as per capita rice expenditure, price of rice per kilogram, rice production, per capita rice consumption, population, and rice crop harvest area, this study seeks to produce more accurate and comprehensive projections. This prediction model is expected to assist the government in identifying provinces that are vulnerable to food shortages, formulating more efficient distribution strategies, and designing evidence-based policies to strengthen national food security.

Although food security has been widely studied, most research is still limited to national descriptive analysis or simple linear models (Allee et al., 2021). In fact, multidimensional data is readily available and has great potential to be processed within a modern predictive framework. This gap becomes even more important when linked to the context of national defense and geopolitics. Using Random Forest Regressor, this study attempts to fill this methodological and empirical gap, while providing a stronger analytical basis for anticipatory food policies.

The novelty of this research lies in the application of the Random Forest Regressor algorithm to predict inter-provincial rice food security in Indonesia by utilizing multidimensional indicators simultaneously. The justification for this research is further strengthened by the fact that food, especially rice, is not merely an economic commodity but also a strategic component of non-military defense. Amid global geopolitical uncertainty, where rice import routes can be disrupted by war or embargoes, food self-sufficiency based on domestic production is a key factor in maintaining national stability. Therefore, this research not only contributes academically by enriching the literature on food security through a machine learning approach, but also contributes practically by providing a predictive model that can support public policy in strengthening food security as a pillar of national defense.

2. RESEARCH METHOD

Research Design

This study uses a quantitative design with a predictive approach based on machine learning. The model chosen is Random Forest Regressor, which is known to be effective in handling non-linear data and capable of integrating multidimensional variables to produce more accurate and stable predictions (Shanmugasundar et al., 2021; Zhou et al., 2023). This design was chosen because it is relevant for identifying complex relationships between variables that affect rice food security in Indonesia at the provincial level. With this approach, the study seeks not only to provide numerical estimates, but also to provide a comprehensive understanding of the main factors that influence disparities in food security between regions.

Population and Research Sample

The research population covers all provinces in Indonesia as the unit of analysis, given that rice food security varies significantly between regions and is a major commodity in national food consumption. The research sample was taken comprehensively (census sampling), as data was available for all provinces, enabling a more holistic analysis of rice food security (BPS, 2025). With this method, differences in food conditions between provinces can be analyzed in detail. The main variables used include six indicators relevant to food security, namely: (1) per capita rice expenditure (Rp) as an indicator of the economic burden of households on food consumption, (2) the price of rice per kilogram (Rp) as a factor in food economic stability, (3) rice production (tons) which indicates the capacity of local food availability, (4) population as a variable of food demand, (5) annual rice consumption per capita (kg) which reflects the level of community dependence on rice, and (6) rice crop harvest area (ha) as a production variable related to land capacity and agricultural efficiency.

Table 1. Research Dataset

Province	Per capita rice expenditure (Rp)	Rice price per kg (Rp)	Rice production (tons)	Population	Annual per capita rice consumption (kg)	Rice crop harvest area (ha)
Aceh	1185756	15670	956278.09	5554800	86.164	301196.35
Sumatera Utara	1375244	15230	1264752.48	15588500	94.692	419463.48
Sumatera Barat	1228240	17420	785425.72	5836200	78.572	295278.98
Riau	1108640	16220	127438.73	6728100	75.244	56421.96
Jambi	1108640	15830	162563.9	2183300	75.244	61625.68
.	.	.	.	.	.	.
.	.	.	.	.	.	.
.	.	.	.	.	.	.
Papua Barat Daya	981136	18440	24.2	616100	46.28	9.66

Data Collection Techniques

This research uses secondary data sourced from official publications by government agencies, specifically the Central Statistics Agency (BPS), the Ministry of Agriculture, and the National Food Agency for 2024. The dataset used is from 2024, which was chosen because it is the most recent and relevant to the current state of national food security. The selection of 2024 also provides a more up-to-date context on post-pandemic conditions, climate change, and global geopolitical dynamics that may affect food supply (BPS, 2025). The collected data was then compiled into tables consisting of columns according to the main variables, namely province, per capita rice expenditure, rice price per kilogram, rice production, population, per capita rice consumption, and rice harvest area. Before being used in the analysis, data preprocessing was carried out, including cleaning the data of recording errors, standardizing measurement units, normalizing values so that they could be compared fairly, and handling missing values so that they would not affect the prediction results.

Data Analysis Techniques

Data analysis was conducted in four main stages. First, exploratory data analysis (EDA) was performed to understand data distribution, rice consumption and production trends, and correlations between variables. This stage was important for detecting initial patterns that could explain the relationship between economic, demographic, and agricultural factors and food security. Second, the dataset was divided into a training set and a test set to build and measure the performance of the prediction model. Third, the Random Forest Regressor algorithm was applied with parameter settings optimized using grid search or cross-validation techniques to improve model performance. This algorithm was chosen because it reduces the risk of overfitting and provides stable prediction results even with complex data. Fourth, the prediction results were evaluated using statistical metrics such as Mean Absolute Error (MAE), Root Mean Square Error (RMSE), and R-squared (R^2) to assess the accuracy, prediction error rate, and reliability of the model. The analysis results are then interpreted to produce projections of interprovincial rice food security, which can ultimately be used as a basis for consideration in formulating strategic policies in the field of food security and national defense.

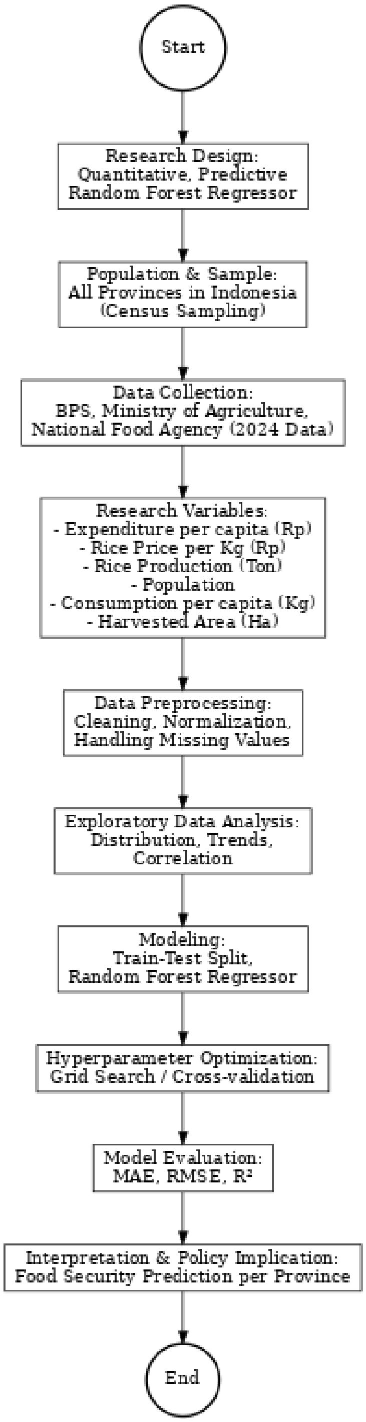

Figure 1. Research Flowchart

The research process began with determining a quantitative predictive research design using the Random Forest Regressor algorithm. All provinces in Indonesia were used as the population and sample for the research using census sampling techniques. The data collected was sourced from official institutions such as the Central Statistics Agency (BPS), the Ministry of Agriculture, and the National Food Agency for 2024, reflecting the latest conditions related to national food indicators. The variables used include per capita rice expenditure, rice price per kilogram, rice production, population, per capita rice consumption, and rice harvest area. After the data was collected, pre-processing was carried out in the form of cleaning, normalization, and handling of missing values so that the data was ready for analysis.

The next step is exploratory data analysis (EDA) to understand the distribution of data, trends, and correlations between variables relevant to rice food security. After that, the dataset is divided into training data and test data to build a prediction model using Random Forest Regressor. Optimization is carried out through grid search or cross-validation to obtain the best parameters. The model is evaluated using the Mean Absolute Error (MAE), Root Mean Square Error (RMSE), and R-squared (R^2) metrics to ensure the accuracy of the predictions. Finally, the prediction results are interpreted to produce an overview of rice food security between provinces as strategic input in the formulation of food and national defense policies.

Random Forest Regressor

Random Forest Regressor is an ensemble learning algorithm that combines multiple Decision Tree Regressors to produce more stable and accurate predictions (Bakır et al., 2024; Salman et al., 2024).

$$\hat{y} = \frac{1}{B}\sum_{b=1}^{B} T_b(x) \tag{1}$$

with:
$\hat{y}$ = final predicted value,
B = number of trees in the forest,
$T_b(x)$ = prediction results from tree-b

Evaluation Metrics

a. Mean Absolute Error (MAE)

Measures the average of the absolute value of the difference between the actual and predicted values (Robeson & Willmott, 2023; Tatachar, 2021):

$$MAE = \frac{1}{N}\sum_{i=1}^{N} |y_i - \hat{y}_i| \tag{2}$$

a. Root Mean Squared Error (RMSE)

A regression evaluation metric that measures the average prediction error by giving greater weight to large errors (Chicco et al., 2021; Hodson, 2022). The formula is:

$$\boldsymbol{RMSE} = \sqrt{\frac{\mathbf{1}}{\boldsymbol{N}}\sum_{\boldsymbol{i}=\mathbf{1}}^{\boldsymbol{N}} (\boldsymbol{y}_{\boldsymbol{i}} - \hat{\boldsymbol{y}}_{\boldsymbol{i}})^{\mathbf{2}}} \tag{3}$$

c. Coefficient Determination ($\boldsymbol{R}^{\mathbf{2}}$)

Assesses how much variation in the target data can be explained by the model (Naidu et al., 2023; Rainio et al., 2024):

$$R^2 = 1 - \frac{\sum_{i=1}^{N}(y_i - \hat{y}_i)^2}{\sum_{i=1}^{N}(y_i - \bar{y}_i)^2}\sum_{i=1}^{N}(y_i - \hat{y}_i)^2 \tag{4}$$

where:

$$\bar{y} = \frac{1}{N}\sum_{i=1}^{N} y_i \tag{5}$$

$R^2 = 1$, means the prediction is perfect.
$R^2 = 0$, means that the model is no better than the average.
It can be negative if the model is very bad.

3. RESULTS AND DISCUSSIONS

Result

The results of this study show that there are disparities in food security between provinces in Indonesia based on data exploration analysis and predictive modeling using Random Forest Regressor. From the results of Exploratory Data Analysis (EDA), it can be seen that provinces with large production bases such as East Java, South Sulawesi, and North Sumatra are in a surplus position because their rice production far exceeds domestic consumption needs. Conversely, provinces with limited agricultural land, such as DKI Jakarta, Riau Islands, and Southwest Papua, tend to experience food deficits and are highly dependent on supplies from other provinces. Correlation analysis reinforces these findings by showing a very strong positive relationship ($r > 0.85$) between rice production and harvest area, indicating that land capacity is a major determinant of rice-based food availability in Indonesia. In addition, the price of rice per kilogram was found to be higher in provinces with low productivity and high per capita consumption, especially in Papua and Maluku, thereby increasing the economic vulnerability of communities in terms of food access. Population size also plays a significant role as it is directly related to total rice consumption; provinces with dense populations such as West Java and East Java, despite being surplus areas, still face major challenges in terms of logistics distribution and stock management. At the modeling stage, the dataset was divided into 80% training data and 20% test data, then the Random Forest Regressor algorithm was used with parameter optimization through grid search to obtain the best results. The optimal parameter combination was found to be n_estimators = 300, max_depth = 12, and min_samples_leaf = 2, which provided the most stable prediction performance for key food security variables. These findings show that the integration of exploratory analysis, inter-indicator correlations, and machine learning-based predictive modeling can provide a comprehensive picture of the distribution of rice surpluses and deficits in Indonesia. Thus, this study not only reveals disparities in food security between provinces but also offers a predictive approach that can be used as a basis for formulating strategic policies in distribution management, price control, and national food production planning. The figure illustrates significant disparities in the rice-based food security index across provinces. Surplus-producing regions such as East Java, South Sulawesi, and North Sumatra demonstrate relatively higher index values, while provinces with limited agricultural capacity, including DKI Jakarta, Riau Islands, and Southwest Papua, exhibit lower values, indicating greater dependency on interprovincial rice distribution.

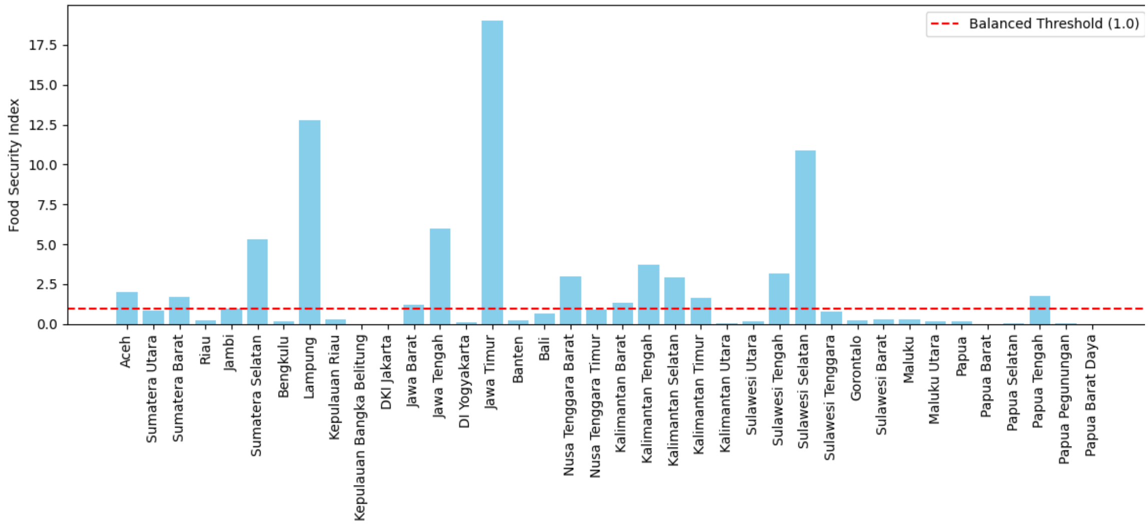

Figure 2. Food Security Index per Province

The Food Security Index values show a clear disparity among Indonesian provinces. Provinces such as *Jawa Timur (19.03)*, *Lampung (12.78)*, and *Sulawesi Selatan (10.88)* are strongly classified as Surplus, indicating that their rice production is far higher than domestic demand. On the other hand, provinces like *DKI Jakarta (0.0019)*, *Papua Barat Daya (0.0008)*, and *Kepulauan Bangka Belitung (0.0003)* are in severe Deficit, suggesting a high dependency on external rice supply. A few provinces, such as *Jambi (0.99)*, fall close to the threshold and are classified as Balanced.

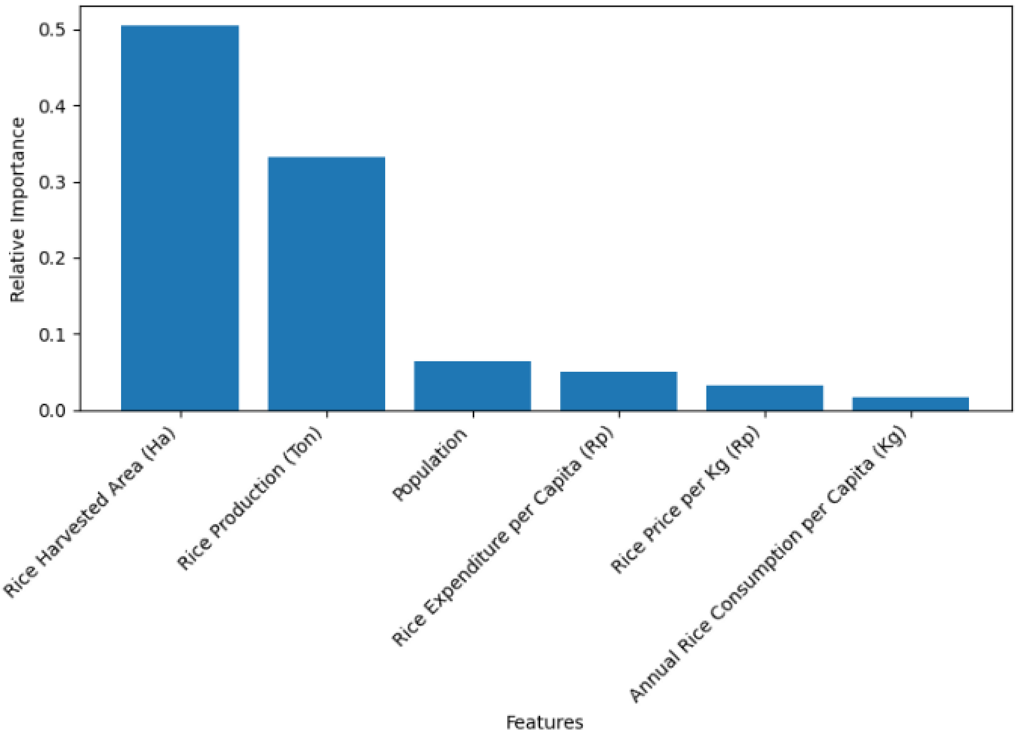

Figure 3. Feature Importance on Food Seucity Index

The Random Forest model analysis reveals critical insights into the determinants of rice-based food security in Indonesia, where supply-side variables clearly dominate the predictive structure. The model highlights that rice harvested area contributes the largest share of importance at 50.5%, followed by rice production at 33.2%. These findings underscore that the extent and productivity of agricultural land are the central pillars in securing stability within the food security index. In contrast, demand-side and socio-economic factors such as population size (6.4%), rice expenditure per capita (5.0%), and rice price per kilogram (3.2%) exert only moderate influence, while annual rice consumption per capita contributes merely 1.6%. This disparity indicates that consumption patterns or purchasing power alone cannot adequately explain inter-provincial variations in food security. Instead, it is the robustness of the supply chain, anchored in agricultural capacity and output, that remains decisive. From a broader perspective, this outcome carries significant implications for non-military national defense. Food insecurity, if left unaddressed, can trigger social unrest, erode community resilience, and ultimately weaken sovereignty, particularly in times of geopolitical disruption when import routes may be threatened by conflict or embargoes. Strengthening domestic agricultural capacity therefore becomes not only an economic necessity but also a strategic imperative for national resilience. By prioritizing land management, yield improvement, and sustainable production systems, Indonesia can enhance its food self-sufficiency, reduce external vulnerabilities, and fortify the foundation of national stability in the face of global uncertainty.

Table 2. Metrics Result

Metrics	Value
MAE	0.8444
RMSE	1.3361
R^2	0.8239

Table 2 presents the performance evaluation of the Random Forest model in predicting the Food Security Index across Indonesian provinces, providing a comprehensive picture of the model's reliability and practical relevance. The Mean Absolute Error (MAE) of 0.8444 suggests that, on average, the model's predictions deviate by less than one unit from the actual observed values, indicating a fairly good level of accuracy in capturing general trends. This level of error is acceptable in the context of complex, multidimensional data involving production, consumption, demographic, and economic variables, and highlights the model's robustness in approximating real-world conditions. The Root Mean Squared Error (RMSE) of 1.3361, however, shows that although the model performs well overall, there are certain provinces where prediction errors are larger, particularly in regions characterized by extreme values of rice production or consumption. Such areas often deviate from the national trend due to unique geographical, demographic, or distributional challenges, making them more difficult to predict accurately. Despite this, the high R-squared (R^2) value of 0.8239 indicates that approximately 82% of the variance in provincial Food Security Index values is successfully explained by the model, underscoring its strong explanatory and predictive power. This high explanatory capacity demonstrates that the selected features—particularly rice harvested area, production, and population—are able to capture the underlying dynamics of food security effectively. Taken together, these results affirm that the Random Forest model is not only statistically reliable but also practically useful in informing policy decisions. The model's outputs can serve as an evidence-based foundation for identifying provinces at risk of food insecurity, guiding distribution strategies, and formulating anticipatory policies. Consequently, it provides valuable insights for strengthening food security governance and supports Indonesia's broader agenda of ensuring national stability and resilience in the face of uncertainty.

Discussions

The results of the study show that there are significant disparities in the food security index between provinces in Indonesia, with several provinces such as East Java, Lampung, and South

Sulawesi experiencing a surplus, while provinces such as DKI Jakarta, Southwest Papua, and the Bangka Belitung Islands are experiencing a severe deficit. This disparity confirms that food security in Indonesia is still greatly influenced by geographical conditions, production structures, and interregional distribution. Provinces with large areas of land and high rice production are automatically able to meet and even exceed domestic demand, while provinces with limited land and high urbanization tend to depend on supplies from outside the region. These findings are in line with the research by Yuliana et al. (2021), which emphasizes that food security in Indonesia is greatly influenced by the spatial distribution of rice production and the capacity of regions to manage agricultural land resources. However, this study makes a new contribution by presenting prediction results based on the Random Forest algorithm, which not only captures factual conditions but also provides quantitative estimates of the extent to which a province has a surplus or deficit. Thus, these results reinforce the argument that agricultural development in Indonesia needs to focus on equalizing the distribution of production between regions, not just increasing national production alone.

Feature importance analysis in the Random Forest model confirms that supply-side variables, namely rice harvest area (50.5%) and rice production (33.2%), are dominant factors in determining the food security index. Meanwhile, demand-side variables such as per capita rice consumption and rice price per kilogram have a relatively small influence. This shows that food supply availability remains a key factor in measuring food security, confirming the classical food security theory that availability is a fundamental dimension. These results are in line with research by Suryana (2019), which states that increased land productivity and production stability are the most influential factors in maintaining food security in Indonesia, more significant than price and consumption factors. However, these results differ from the study by Rahman & Saptana (2020), which highlights purchasing power and household expenditure as the main determinants of food insecurity. This difference indicates diverse contexts: the research by Rahman & Saptana focuses more on the household level, while this research highlights dynamics at the provincial level. Thus, this research contributes to enriching the literature by emphasizing the importance of a multi-level perspective in food security studies.

The performance of the Random Forest model in this study was relatively good, with an MAE value of 0.8444, an RMSE of 1.3361, and an R^2 of 0.8239, which means that approximately 82% of the variation in the food security index between provinces can be explained by the model. This accuracy shows that the model is capable of representing the complex relationship between production, consumption, and economic factors on the food security index. Compared to previous studies that used classical econometric approaches or multiple linear regression, the accuracy of this model is relatively higher. For example, research by Hidayat et al. (2020) using linear regression to predict rice availability was only able to explain about 65% of the data variation, indicating the limitations of traditional methods in capturing non-linear patterns. Thus, the application of machine learning in this study provides significant methodological advantages, especially in processing data with high variability between regions. Furthermore, the results of this study are in line with the findings of Putri & Ananda (2022), which emphasize that ensemble learning-based algorithms such as Random Forest tend to provide more stable and accurate prediction results in the context of agriculture. Therefore, this study not only confirms the relevance of the machine learning approach to food security studies, but also opens up space for further research that can integrate environmental variables, climate change, and interregional trade dynamics into a more comprehensive prediction model.

4. CONCLUSION

This study confirms that rice food security in Indonesia still faces significant inter-provincial disparities. The results of the analysis using the Random Forest Regressor algorithm show that supply-side factors, particularly harvest area and rice production, are the main determinants of the food security index, while demand-side factors such as price and per capita expenditure have relatively less influence at the provincial level. This condition shows that there are surplus areas such as East Java, Lampung, and South Sulawesi that support the national food system, as well as deficit areas such as DKI Jakarta, Papua, and the Bangka Belitung Islands that are highly vulnerable to supply disruptions.

These findings address the initial problem that even though government food programs are already in place, disparities between provinces remain and have the potential to weaken national food self-sufficiency. Furthermore, this study emphasizes that food is not only an economic and social issue, but also a pillar of non-military defense. Dependence on certain provinces and imports creates serious vulnerability if distribution channels are disrupted by disasters, conflicts, or global embargoes. Thus, the application of machine learning-based predictive models such as Random Forest can serve as a strategic instrument for mapping risks, anticipating vulnerable areas, and formulating more adaptive food distribution and reserve policies. This is in line with the urgency outlined in the introduction, that strengthening data-based food security prediction systems is urgently needed not only to support the achievement of Zero Hunger (SDGs), but also to strengthen Indonesia's sovereignty and national resilience amid global geopolitical dynamics.

REFERENCES

Alifnur Harmawan, R., & Mulyati, E. (2024). Challenges and Strategies for Rice Price Stability: A Systematic Review of Supply Chain Dynamics in Indonesia During Critical Periods. *DIVERsITY: FOsTERING UNITY SUsTAINABLE REsEARCH AND INNOVATION SOCIETY*, 468–476. https://pns.mypolycc.edu.my/index.php/program/category/139-iric

Allee, A., Lynd, L. R., & Vaze, V. (2021). Cross-national analysis of food security drivers: comparing results based on the Food Insecurity Experience Scale and Global Food Security Index. *Food Security*, *13*(5), 1245–1261. https://doi.org/10.1007/s12571-021-01156-w

Alta, A. (2023). *Memodernisasi Pertanian Indonesia*. PT. RajaGrafindo Persada-Murai Kencana. https://books.google.com/books?hl=en&lr=&id=KFvTEAAAQBAJ&oi=fnd&pg=PA1&dq=memodernisasi+pertanian+indonesia&ots=FJfIjTx65S&sig=7Ru3Lsed057Cwq63ZIjeD_xftmw

Atukunda, P., Eide, W. B., Kardel, K. R., Iversen, P. O., & Westerberg, A. C. (2021). Unlocking the potential for achievement of the un sustainable development goal 2 – 'zero hunger' – in Africa: Targets, strategies, synergies and challenges. *Food and Nutrition Research*, *65*, 10–29219. https://doi.org/10.29219/fnr.v65.7686

Bakır, R., Orak, C., & Yüksel, A. (2024). Optimizing hydrogen evolution prediction: A unified approach using random forests, lightGBM, and Bagging Regressor ensemble model. *International Journal of Hydrogen Energy*, *67*, 101–110. https://doi.org/10.1016/j.ijhydene.2024.04.173

Ben Hassen, T., & El Bilali, H. (2022). Impacts of the Russia-Ukraine War on Global Food Security: Towards More Sustainable and Resilient Food Systems? *Foods*, *11*(15), 2301. https://doi.org/10.3390/foods11152301

BPS. (2025). *Produksi Padi dan Beras Menurut Provinsi, 2024*.

Chicco, D., Warrens, M. J., & Jurman, G. (2021). The coefficient of determination R-squared is more informative than SMAPE, MAE, MAPE, MSE and RMSE in regression analysis evaluation. *PeerJ Computer Science*, *7*, 1–24. https://doi.org/10.7717/PEERJ-CS.623

Clapp, J., Moseley, W. G., Burlingame, B., & Termine, P. (2022). Viewpoint: The case for a six-dimensional food security framework. *Food Policy*, *106*, 102164. https://doi.org/10.1016/j.foodpol.2021.102164

Cook, A. D. B., & Nair, T. (2021). Non-traditional security in the Asia-pacific: A decade of perspectives. In *Non-traditional Security In The Asia-pacific: A Decade Of Perspectives*. World Scientific. https://doi.org/10.1142/11941

Fitrawaty, Hermawan, W., Yusuf, M., & Maipita, I. (2023). A simulation of increasing rice price toward the disparity of income distribution: An evidence from Indonesia. *Heliyon*, *9*(3). https://doi.org/10.1016/j.heliyon.2023.e13785

Fristin, Y., & Supanto, F. (2021). Development Model of Rice Supply Chain Management to Ensure Self-Sufficiency and Food Security. *Jurnal Bisnis Dan Manajemen*, *8*(2), 353–366. https://doi.org/10.26905/jbm.v8i2.6320

Hidayana, D., Yusgiantoro, P., Midhio, W., Saragih, H. J., & Wijaya, A. R. (2022). Climate Change, Food Insecurity, and National Defense in Archipelago Country: An Interlinked Challenges for

Indonesia. *Journal of Positive School Psychology*, *2022*(5), 5412–5424. http://journalppw.com

Hodson, T. O. (2022). Root-mean-square error (RMSE) or mean absolute error (MAE): when to use them or not. *Geoscientific Model Development*, *15*(14), 5481–5487. https://doi.org/10.5194/gmd-15-5481-2022

Larasati, K. K., & Hana, A. (2025). Challenges and Legal Strategies of Indonesia in Global Trade Agreements in the Era of Fragmentation. *LIBERATICA*, *27*(1), 12–22.

Naidu, G., Zuva, T., & Sibanda, E. M. (2023). A Review of Evaluation Metrics in Machine Learning Algorithms. *Lecture Notes in Networks and Systems*, *724 LNNS*, 15–25. https://doi.org/10.1007/978-3-031-35314-7_2

Pachapur, P. K., Pachapur, V. L., Brar, S. K., Galvez, R., Le Bihan, Y., & Surampalli, R. Y. (2020). Food Security and Sustainability. *Sustainability: Fundamentals and Applications*, 357–374. https://doi.org/10.1002/9781119434016.ch17

Rainio, O., Teuho, J., & Klén, R. (2024). Evaluation metrics and statistical tests for machine learning. *Scientific Reports*, *14*(1), 6086. https://doi.org/10.1038/s41598-024-56706-x

Robeson, S. M., & Willmott, C. J. (2023). Decomposition of the mean absolute error (MAE) into systematic and unsystematic components. *PLoS ONE*, *18*(2 February), e0279774. https://doi.org/10.1371/journal.pone.0279774

Salman, H. A., Kalakech, A., & Steiti, A. (2024). Random Forest Algorithm Overview. *Babylonian Journal of Machine Learning*, *2024*, 69–79. https://doi.org/10.58496/bjml/2024/007

Shanmugasundar, G., Vanitha, M., Čep, R., Kumar, V., Kalita, K., & Ramachandran, M. (2021). A comparative study of linear, random forest and adaboost regressions for modeling non-traditional machining. *Processes*, *9*(11), 2015. https://doi.org/10.3390/pr9112015

Tatachar, A. V. (2021). Comparative Assessment of Regression Models Based On Model Evaluation Metrics. *International Research Journal of Engineering and Technology*, *8*(9), 853–860. www.irjet.net

Widowati, S., Winarti, C., Hoerudin, & Tjahjohutomo, R. (2024). Recommendations for addressing quality issues of government rice reserve: Indonesia case study. *BIO Web of Conferences*, *119*, 2009. https://doi.org/10.1051/bioconf/202411902009

Yusrin, N. A. (2023). the Analysis of Rice Massive Importing in Indonesia Based on Macroeconomics, Microeconomics, International Economics and Politic Economics. *Ultima Management : Jurnal Ilmu Manajemen*, *15*(2), 308–329. https://doi.org/10.31937/manajemen.v15i2.3411

Zhou, Z., Qiu, C., & Zhang, Y. (2023). A comparative analysis of linear regression, neural networks and random forest regression for predicting air ozone employing soft sensor models. *Scientific Reports*, *13*(1), 22420. https://doi.org/10.1038/s41598-023-49899-0